

SURVEY OF IMAGE SEGMENTATION AND CLASSIFICATION USING MARKOV RANDOM FIELD

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ABSTRACT

This paper presents a multiresolution image segmentation method based on the sampling method and Markov random field (MRF) modeling. A major contribution of this work is to add sampling approach to the segmentation algorithm producing the same segmentation pattern at different resolutions. The multiresolution technique is one of the most important techniques for image segmentation and proposes a new image segmentation model by incorporating the multiregion-sampling and the Markov random field model. Experiments are conducted using synthetic aperture radar data and remote sensing images, which demonstrates that our method can improve the segmentation accuracy compared with the multiresolution method based on the pixel level. The proposed method is more computationally efficient as compared to standard Markov random field (MRF) models. Furthermore, the proposed MRS-MRF algorithm estimates the number of regions in the image in an unsupervised fashion. The effectiveness of the proposed MRS-MRF algorithm is illustrated using synthetic and real data.

KEYWORDS: Image Segmentation, Sampling Method, Markov Random Field (MRF), Multiresolution Technique, Region

INTRODUCTION

Image segmentation is the process of partitioning a digital image into multiple segments (sets of pixels, also known as super pixels). The goal of segmentation is to simplify and change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics.

The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image. Each of the pixels in a region is similar with respect to any characteristic or computed property, such as color, intensity or texture. Adjacent regions are significantly different with respect to the same characteristic (s). When applied to a stack of images, typically in medical imaging, the resulting contours after image segmentation can be used to create 3D reconstructions with the help of interpolation algorithms like Marching cubes.

During multi resolution segmentation strategies, current transformation is wide familiar categorical the multi resolution representation of images since it has the favorable mathematical foundation and regular pyramid structure. However, current transformation could be a down sampling method at the pixel level, which can only describe the linear and local patterns of images. It limits the accuracy of the multiresolution segmentation approaches.

Recently, region-based segmentation methods are proposed with the purpose of modeling complex and macro texture patterns. These methods usually can reduce the misclassifications of pixel-based results since they use

the over segmented region as the basic unit. In this letter, motivated by this idea, we extend the multiresolution representation of the pixel level to the region level. Furthermore, by incorporating the region-based representation and the MRF model, we propose a multiregion-sampling MRF (MRS-MRF) model for image segmentation. It is possible for this model to capture and utilize the more complex and macro texture pattern information of images at different resolutions, which may make the MRS-MRF resist the heavy noise and recognize objects whose appearances have a large range of variations.

MULTIREGION-RESOLUTION REPRESENTATION

The multi resolution representation is the fundamental step for multi resolution segmentation approaches. It decomposes the original image Y into vector images on each resolution $Y^{(n)}$ ($1 \leq n \leq N$) and obtains an N -level representation $Y = \{Y^{(1)}, Y^{(2)}, \dots, Y^{(N)}\}$. Furthermore, the vector image $Y^{(n)}$ is usually composed of a low-frequency coefficient image $Y^{(n)L}$ and a high frequency coefficient image $Y^{(n)H}$, where $Y^{(n)L}$ describes the rough information about a given image on the n th resolution and $Y^{(n)H}$ describes the detail information. The representations are usually obtained at the pixel level, since the spatial context among pixels is regular. However, it can consider the local texture pattern of images.

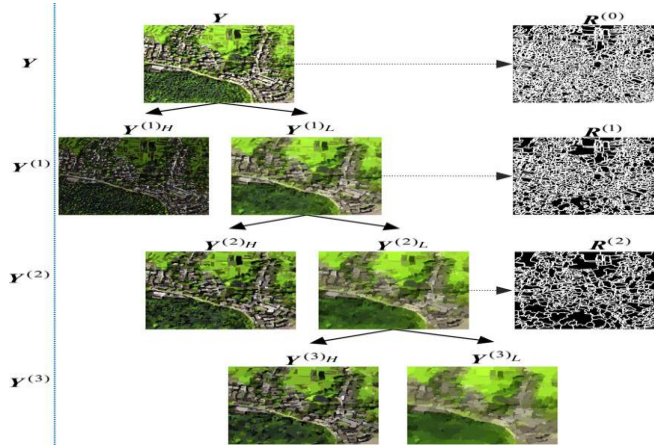


Figure 1: Example of Multiregion-Resolution Representation with Three-Level Decomposition

According to figure.1, the original image is decomposed into three levels. From this example, one can see that the size of regions in the oversegmented region sets $R^{(n)}$ ($0 \leq n \leq N-1$) shows an increasing trend since the feature of each $R^{(n)}$ averages the features of $R^{(n-1)}$ and its neighboring regions. Therefore, the corresponding $Y^{(n)}$ can describe the larger texture pattern of a given image.

REVIEW OF LITERATURE

Our study of various research and journal papers related to image segmentation and classification based on Markov Random Field. Here we discuss some methods along with their respective work contribution and title.

Chen Zheng, Leiguang Wang, Rongyuan Chen, and Xiaohui Chen[1] propose a new image segmentation model by incorporating the multi region-resolution and the Markov random field model. Wavelet transformation is a pixel-based method and is widely used for multi resolution segmentation approaches, but it suffers the shortage of modeling the macro texture pattern of a given image and this method can improve the segmentation accuracy compared with the multi resolution method based on the pixel level.

By combining it with the MRF model a novel MRR-MRF model is designed for image segmentation. Compared

with fixed multi resolution techniques, the multi region-resolution technique uses the over segmented regions as the basis units to realize decomposition. Hence, the multi region-resolution representation can describe the complex and macro texture patterns of a given image. It can make the MRR-MRF oppose noise and model more texture information

Quan Zhou, Jun Zhu, and Wenyu Liu [2] present an active hybrid Markov random field (DHMRf), which clearly captures middle-level object shape and low-level visual look (e.g., texture and color) for image labeling. Each node in DHMRf is described by either a deformable template or an appearance model as visual prototype. On the other hand, the edges encode two types of intersections: co-occurrence and spatial layered context, with respect to the labels and prototypes of connected nodes. To learn the DHMRf model, an iterative algorithm is designed to automatically select the most informative features and estimate model parameters. The algorithm achieves high computational efficiency since a branch-and-bound schema is introduced to estimate model parameters and finally present a DHMRf model to address the challenges of incorporating explicit shape templates as well as appearance models into a probabilistic multi-class image segmentation framework. At the time of experiments these methods have been tested on two datasets: MSRC 21-class and LHI 15-class dataset and evaluate the results in terms of pixel-wise segmentation accuracy. Despite achieving state-of-the-art accuracy, we believe that even better results can be obtained by taking appearance cues and shape features jointly into account to model structured objects and also interested in hierarchical part-based shape model, for structured objects to cope with inter- or self-occlusion, while retaining high efficiency and accuracy.

Guokang Zhu, Qi Wang, Yuan Yuan and Pingkun Yan [3] present a new psycho logic visual feature based on differential threshold and applies it in a supervised Markov-random-field framework. The reliable detection of salience can help a lot of useful processing without past knowledge about the scene, such as content-aware image compression, segmentation, etc. Even if many efforts have been spent on this subject, the feature expression and model construction are further from perfect. The obtained saliency maps are therefore not satisfying enough. In order to overcome these challenges and at the conclusion end present a supervised method for saliency detection has been presented. The proposed method mainly incorporates the single purely inspired saliency feature, differential threshold based color feature, to expect the possibilities of each pixel being salient through MRF learning. Its performance has been evaluated on two public image data sets and the proposed method outperforms other 14 state-of-the-art saliency detection methods in terms of both effectiveness and robustness. An application of seam carving is also involved, which intuitively exemplifies the usefulness of the proposed method.

Pedram Ghamisi, Jón Atli Benediktsson, Fellow, and Magnus Orn Ulfarsson [4] proposed a new automatic framework for the classification of hyper spectral images is proposed. The new method is based on combining hidden Markov random field segmentation with support vector machine (SVM) classifier. In order to preserve limits in the final classification map, a slope step is taken into account.

Hyper spectral remote sensing technology allows one to obtain a sequence of possibly hundreds of contiguous spectral images from ultraviolet to infrared. Square spectral classifiers treat hyper spectral images as a list of spectral measurements and do not consider spatial dependencies, which leads to a theatrical decrease in classification accuracies and finally a fully automated framework which takes into account both spectral information and spatial information has been introduced for classification of hyper spectral images. In the framework, SVM is used for the extraction of spectral information. In parallel, HMRf-EM is used for the removal of spatial information.

The efficiency of the proposed method is tested in both situations with and without considering the gradient step. The proposed method is evaluated on two data sets (Indian Pines and Salinas). In both cases, the new approach

outperforms other studied methods. It should be noted that the concept of HMRF is used for the first time in the field of remote sensing in this paper, and the efficiency of that for the segmentation of hyper spectral images is demonstrated. Finally, it is shown in this paper that the method performs well in terms of accuracies compared with the state of the art. In addition, the proposed approach is fully automatic and user-friendly in comparison to most of the methods.

Maoguo Gong, Member, Linzhi Su, Meng Jia, and Weisheng Chen [5] present a new approach for change detection in synthetic aperture radar (SAR) images. The approach classifies changed and unchanged regions by fuzzy c-means (FCM) clustering with a novel Markov random field (MRF) energy function. In order to reduce the effect of disfigure noise, a novel form of MRF energy function with an additional term is established to modify the membership of each pixel and the degree of modification is determined by the relationship of the neighboring pixels. The specific form of the additional term is dependent on different situations, and is established ultimately by utilizing the least square method; their contributions lie in two aspects.

Firstly, in order to reduce the effect of spoil noise, the proposed approach focuses on modifying the membership instead of modifying the objective function. It is computationally simple in all the steps involved. Its objective function can just return to the original form of FCM, which leads to its less time consumption than that of some recently improved FCM algorithms obviously. Secondly, the proposed approach modifies the membership of each pixel according to a novel form of MRF energy function through which the neighbors of each pixel as well as their relationship are concerned with. Theoretical analysis and experimental results on real SAR datasets show that the proposed approach can detect the real changes as well as mitigate the effect of speckle noises

Ken Xu, Wen Yang, Member, Gang Liu, and Hong Sun [6] present an efficient unsupervised semantic classification method for high-resolution satellite images and add label cost, which can discipline a solution based on a set of labels that appear it by optimization of energy, in the random fields on hidden topics, and an iterative algorithm is thereby proposed to make the number of classes finally be converted to a proper level. Compared with other mentioned classification algorithms, this method not only can obtain accurate semantic segmentation results by larger scale structures but also can automatically assign the number of segments and at the reach at the destination end find out an unverified semantic classification algorithm has been proposed for high-resolution satellite images. The iterative algorithm based on label cost and BIC can automatically determine the number of classes in the classification. It can keep the consistency of the semantics as well. The evaluation over four scenes has shown that the proposed method achieves better classification performance.

Olivier Eches, Jón Atli Benediktsson, Fellow, Nicolas Dobigeon and Jean-Yves Tournet [7] propose the MRF sites regions. These regions have built a self-complementary area filter that stems from the morphological theory. This kind of filter divides the original image into flat zones where the basic pixels have the same spectral values. Once the MRF has been clearly established, a hierarchical Bayesian algorithm is proposed to estimate the abundances, the class labels, the noise variance, and the corresponding hyperparameters. A hybrid Gibbs sampler is constructed to generate samples according to the corresponding posterior distribution of the unknown parameters and hyperparameters. Recent works have shown that exploiting spatial dependencies between image pixels can improve spectral unmixing. Markov random fields (MRF) are classically used to model these spatial correlations and partition the image into multiple classes with homogeneous abundances. Finally, a fully Bayesian approach jointly estimating the end member matrix, the similarity regions and the other parameters of interest would deserve to be investigated.

Dorit S. Hochbaum [8] presents an algorithm that solves the problem in polynomial time when the deviation

function is convex and separation function is linear; and in strongly polynomial time when the deviation cost function is linear, quadratic or piecewise linear convex with a few pieces (where “few” means a number exponential in a polynomial function of the number of variables and constraints).

At Markov random field problems, there is also a pairwise relationship between the objects. The objective in Markov random field problem is to minimize the sum of the deviation cost function and a penalty function that grows with the distance between the values of the related pairs separation function.

Oh-Woog Kwon and Jong-Hyeok Lee [9] propose a Web page classifier based on an edition of k-Nearest Neighbor (k-NN) approach. To improve the performance of k-NN approach, we supplement k-NN approach with a feature selection method and a term-weighting scheme using markup tags, and reform document similarity measures used in the vector space model and find out the similarity measure proved successful to improve the efficiency of k-NN approach. And also, the use of feature selection in k-NN approach improved the performance in the validation test.

Renqi Zhang, Wanli Ouyang, Wai-Kuen Cham [10] develop a new edge detecting technique using 3-D Hidden Markov Model and his proposed model can not only capture the relationship of the wavelet coefficients inter-scale, but also consider the intra-scale dependence. A computationally efficient maximum likelihood (ML) estimation algorithm is employed to compute parameters and the hidden state of each coefficient is discovered by maximum a posteriori (MAP) estimation and his model has the potential to be an efficient multi-scale arithmetical modeling tool for another image or video processing tasks.

Zhuowen Tu And Xiang Bai [11] propose a learning algorithm, auto-context. Given a set of training images and their corresponding label maps, they first learn a classifier on local image patches. The classification confidence maps created by the learned classifier are then used as context information, in addition to the original image patches, to train a new classifier. The algorithm then iterates until convergence. Auto-context integrates low-level and context information by fusing a large number of low-level appearance features with context and unspoken shape information. The resulting discriminative algorithm is general and easy to implement. Under nearly the same parameter settings in training they apply the algorithm to three challenging vision applications: background segregation, human body configuration estimation, and scene region labeling. Moreover, context also plays a very important role in medical/brain images where the anatomical structures are mostly constrained to relatively fixed positions.

José M. P. Nascimento And José M. Bioucas-Dias [12] introduce a new unverified hyper spectral un mixing method conceived to linear but highly mixed hyper spectral data sets, in which the simplex of minimum volume, usually estimated by the purely geometrically based algorithms, is future way from the true simplex connected with the end members. The proposed method, an extension of his previous studies, resorts to the numerical framework. The wealth fraction prior is a mixture of Dirichlet densities, thus automatically enforcing the constraints on the abundance fractions imposed by the acquisition process, namely, non negativity and sum-to-one. A cyclic minimization algorithm is developed where the following is observed: 1) The number of Dirichlet modes is inferred based on the minimum description length principle; 2) a generalized probability maximization algorithm is derived to suppose the model parameters; and 3) a sequence of augmented Lagrangian based optimizations is used to compute the signatures of the end members.

Yi Yang, Sam Hallman, Deva Ramanan and Charless C. Fowlkes [13] give the concept about layered model for object detection and image segmentation and describe a generative probabilistic model that composites the output of a bank of object detectors in order to define shape masks and explain the look, depth ordering, and labels of all pixels in an image. Particularly, these system estimates both class labels and object instance labels. Building on previous benchmark criteria

for object detection and image segmentation and define a novel score that evaluates both class and instance segmentation.

Fahmi Khalifa, Garth M. Beache, Georgy Gimel'farb, Guruprasad A. Giridharan, And Ayman El-Baz [14] propose a new automatic framework for analyzing the wall thickness and thickening function of these images that consists of three main steps. First, inner and outer wall borders are segmented from their surrounding tissues with an arithmetical deformable model guided by a special stochastic speed relationship. The latter accounts for Markov-Gibbs shape and appearance models of the object-of-interest and its background. In the second step, point to- point correspondences between the inner and outer borders are found by solving the Laplace equation and provide initial estimates of the local wall thickness and the thickening function index.

Finally, the effects of the segmentation error are reduced and a continuing analysis of the LV wall thickening is performed through iterative energy minimization using a generalized Gauss Markov random field (GGMRF) image model.

Luiz F. S. Coletta, Lucas Vendramin, Eduardo Raul Hruschka, Ricardo J. G. B. Campello, And Witold Pedrycz [15] give the some extension of the two FCM-based clustering algorithms used to cluster distributed data by arriving at some positive ways of determining important parameters of the algorithms (including the number of clusters) and forming a set of systematically structured guidelines such as a selection of the specific algorithm depending on the nature of the data environment and the assumptions being made about the number of clusters. A thorough complexity analysis, including space, time, and communication aspects, are reported.

Yuliya Tarabalka, James C. Tilton, Jón Atli Benediktsson and Jocelyn Chaussonot [16] proposed and investigate the use of automatically selected markers and a novel Marker-based HSEG (M-HSEG) method for spectral-spatial classification of hyper spectral images is proposed. Two classification-based approaches for automatic marker selection are adapted and compared for this purpose. Then, a novel controlled marker-based HSEG algorithm is applied, resulting in a spectral-spatial classification map. Three different implementations of the M-HSEG method are proposed and their performances in terms of classification accuracies are compared at the conclusion end HSEG segmentation approach is one of the few state-of-art segmentation algorithms that both naturally exploits spectral and spatial information and produces a hierarchical set of image segmentations. Many application areas can greatly benefit from methods able to automatically analyze segmentation hierarchies and select a single optimum segmentation level.

PROBLEM STATEMENT

In before we study about various image segmentation method using MRF (Markov Random Filed) and we find out in previous paper describe the method of pixel base and region base segmentation and classification scheme, but not elaborate percentage of area covered by different set of classes and number of object belong to particular class so here we design a method to classify and find the percentage of area covered in the image based on identified regions and find the number of objects in the each basic region.

PROPOSED METHODOLOGY

To find out the various regions we have applied multiregion-resolution (MRR) MRF. Multiregion-sampling (MRS) MRF will classify the major regions of the input images. Further we calculate the area covered by each regions using following.

- Find all regions using MRR-MRF
- Prepare mask of first region

- Apply mask on image
- Binaries the image
- Calculate the area
- Prepare the next region mask
- Repeat the step 3 to 7 till all regions area calculated

In Next Step we Find the Objects in Each Region.

- Prepare mask of region and apply on the image
- Calculate the number of objects using following
 - Search for the next unlabeled pixel, p.
 - Use a flood-fill algorithm to label all the pixels in the connected component containing p.
 - Repeat steps 1 and 2 until all the pixels are labeled.

FORMULATION OF RESEARCH HYPOTHESIS WITH EXPECTED OUTCOMES

There are now a wide variety of image segmentation techniques, some considered general purpose and some designed for specific classes of images. Each of the major classes of image segmentation techniques is defined and several specific examples of each class of algorithm are described. The techniques are illustrated with examples of segmentations performed on real images. Our proposed methodology, improved performance of detection and improved analysis quality of digital image.

Expected outcomes of our research work

- Compare outcome region result in previous as well as proposed scheme
- We get percentage of area covered in old method as well as proposed scheme
- Identify number of objects belongs in particular region both cases
- Analyze Time complexity and space complexity in pervious algorithm as well as proposed scheme.
- Reduced computation time
- Gives a novel method for image segmentation and classification in current technology

THE PROPOSED PLAN OF WORK

The proposed plan of our research works according to our university rule and regulation. But some tentative plans for our work is

- Compare all image segmentation technique in different nature regions.
- Design and formulate our problem and find the approach of solution
- Validate through mathematical model for our design
- Implement our method in providing software by laboratory research

- Published paper in reputed journal and conference for the authentication from our work.

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